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Insurance and Inequality in Sub-Saharan Africa: Policy Thresholds [1]

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Insurance and Inequality in Sub-Saharan Africa: Policy Thresholds

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Abstract

In this study, we examine how insurance affects income inequality in sub-Saharan Africa, using data from 42 countries during the period 2004-2014. Three inequality variables are used, namely: the Gini coefficient, the Atkinson index and the Palma ratio. Two insurance premiums are employed, namely: life insurance and non-life insurance. The empirical evidence is based on the Generalized Method of Moments (GMM). Life insurance increases the Gini coefficient and increasing life insurance has a net positive effect on the Gini coefficient and the Atkinson index. Non-life insurance reduces the Gini coefficient and increasing non-life insurance has a net positive effect on the Palma ratio. The analysis is extended to establish policy thresholds at which increasing insurance premiums completely dampen the net positive effects. From the extended analysis, 7.500 of life insurance premiums (% of GDP) is the critical mass required for life insurance to negatively affect inequality, while 0.855 of non-life insurance premiums (% of GDP) is the threshold required for non-life insurance to negatively affect inequality. Policy thresholds are provided at which insurance penetration decreases income inequality in sub-Saharan Africa.

JEL Classification: I28; I30; I32; O40; O55

Keywords: Insurance; Inclusive development; Africa; Sustainable Development

1. Introduction

The motivation for assessing the relevance of insurance on inequality in sub-Saharan Africa (SSA) is threefold, notably: (1) growing exclusive development and challenges to the post-2015 development agenda; (2) the potential for insurance penetration on the continent; and (3) gaps in the literature. Elements of the motivation are expanded in the same order as they are highlighted.

First, in the light of Sustainable Development Goals (SDGs) pertaining to inequality, the recent evidence of growing exclusive development in Africa represents a policy syndrome in the global challenge of reducing inequality and promoting shared economic prosperity[2]. In essence, inequality is crucial in the objective of enhancing shared economic development for the attainment of most goals enshrined in the post-2015 development agenda. For instance, in order to curtail extreme poverty to a below 3% threshold by 2030, inequality has to be mitigated because the response of extreme poverty to growth decreases with growing levels of inequality (Asongu & Kodila-Tedika, 2017). It has become apparent that inequality in SSA represents a very challenging policy syndrome if most inequality-related SDGs are to be achieved for the continent. The foundations of this assertion are threefold: (1) the established evidence that the response of poverty to growth is a negative function of inequality (Fosu, 2015); (2) Africa has been enjoying more than two decades of growth resurgence (Tchamyou, 2019, 2020); and (3) about 50% of African countries did not attain the Millennium Development Goals (MDGs) extreme poverty target (Asongu & le Roux, 2019).

Two main insights from the above account merit critical examination. On the one hand, the fact that the numerical value of the population still living in extreme poverty has consistently increased in Africa is clear evidence that the economic prosperity has not largely benefited the poor segments of the population. The role of inequality in decreasing the effect of economic growth on poverty reduction can explain why poverty levels in Sub-Saharan Africa are still high despite the recent two decades of economic growth resurgence. Hence, with consideration to the importance of inequality in poverty-growth relationship: "*Output may be growing, and yet the mass of the people may be becoming poorer*" (Lewis, 1955). On the other hand, even in a scenario where 2000-2010 growth levels are maintained in order to achieve the SDGs poverty targets as argued by a stream of the literature (Ravallion, 2013), inequality will need to be dealt with in order to avoid growing extreme poverty and slowing

[2]Policy syndrome within the framework of this study is inequality. This conception and understanding of a policy syndrome is consistent with recent inclusive development (Asongu & Nwachukwu, 2017a) and inequality (Tchamyou *et al.*, 2019a) literature.

down of economic prosperity (Chandy *et al*., 2013; Yoshida *et al*., 2014). The contemporary relevance of addressing inequality in order to achieve most 2030 targets for Africa is consistent with the conclusions of Bicaba *et al*. (2017): "*This paper examines its feasibility for Sub-Saharan Africa (SSA), the world's poorest but growing region. It finds that under plausible assumptions extreme poverty will not be eradicated in SSA by 2030, but it can be reduced to low levels through high growth and income redistribution towards the poor segments of the society*" (p. 93). This assertion on Sub-Saharan Africa is relevant to North African countries (Ncube *et al*., 2014). The purpose of this research is to assess how the policy syndrome of inequality can be addressed with enhanced insurance penetration.

Second, a high potential for insurance penetration in Africa represents a policy instrument with which some macroeconomic and human development outcomes can be achieved. As maintained by Kyerematen (2015), the penetration of insurance in Africa is substantially low relative to other regions of the world. The author supports the perspective by articulating that, with the exception of South Africa, only about 5% of the population in Africa has access to insurance services. Enhanced insurance penetration can potentially reduce inequality because as recently documented by the OECD (2017), insurance policies that are complemented with simplified claims and wide coverage can improve access to financial protection for hitherto underserved segments of society. Unfortunately, the extant literature has failed to examine the relevance of enhancing insurance in the development of poor segments of society in Africa.

Third, as expanded in section 2, the bulk of the literature on insurance penetration in Africa has focused on two main strands, notably: (1) connections between insurance penetration and development outcomes (Ioncică *et al*., 2012; Akinlo, 2015; Alhassan & Biekpe, 2015, 2016a; Asongu & Odhiambo, 2020a); and (2) determinants of insurance penetration (Zerriaa *et al*., 2017; Guerineau & Sawadogo, 2015; Alhassan & Biekpe, 2016b; Asongu & Odhiambo, 2020b). This research extends the former strand of the literature by investigating the relevance of enhancing insurance on inequality because of an apparent gap in the inequality literature. Accordingly, the contemporary inequality literature on Africa has focused on *inter alia*: the nexuses between finance, education and inequality (Meniago & Asongu, 2018; Tchamyou, 2019, 2020); the reinvention of foreign aid for inclusive development (Page & Söderbom, 2015; Jones & Tarp, 2015; Asongu, 2016); the relationships between inequality and corruption (Sulemana & Kpienbaareh, 2018); the nexuses between income, consumption and wealth of poor segments of society (De Magalhães & Santaeulàlia-

Llopis, 2018); and the connection between inequality and foreign investment (Kaulihowa & Adjasi, 2018).

We fully understand the risk involved in doing measurement without firmly established theoretical underpinnings. However, we also argue that applied econometrics should not exclusively be contingent on the rejection and acceptance of established theoretical models. According to the study, applied econometrics, even in the absence of a formal theoretical framework, is a useful scientific research because the findings could provide the basis for theoretical-building. This argument is in accordance with the attendant literature on the relevance of applied econometrics in academic and policy-making circles (Costantini & Lupi, 2005; Narayan *et al.*, 2011; Asongu & Nwachukwu, 2016a). The intuition for the connection between insurance and inequality is based on the perspective that insurance provides leverage against negative household and economic shocks, which can substantially diminish the quality of wellbeing and livelihood. Furthermore, like inflation, this negative shock is more likely to be unfavorably borne by poorer factions of the population, compared to their rich counterparts. Accordingly, improved access to insurance services has the prospect of reducing inequality because it offers financial protection to all segments of society, including the previously underserved categories (OECD, 2017).

The above intuition motivating the study is assessed using a panel of 42 countries in Sub-Saharan Africa. The findings of the study reveal that life insurance has a positive impact on the Gini coefficient whereas increasing life insurances engenders a net positive impact on both the Atkinson index and the Gini coefficient. While non-life insurance mitigates the Gini coefficient, the incidence of increasing non-life insurance on the Palma ratio is positive. An extended analysis is performed to establish policy-relevant thresholds of insurance at which the established positive net impacts on inequality are nullified. From the extended analysis, it is established that: (i) 7.500 of life insurance premium (% of GDP) is the threshold needed for life insurance to influence inequality negatively and (ii) 0.855 of non-life insurance premium (% of GDP) is the threshold required for non-life insurance to impact inequality negatively in the sampled countries.

The rest of the study is structured as follows. Section 2 contains a review of the extant literature while the data and methodology are discussed in section 3. Section 4 discloses the empirical results whereas section 5 concludes with future research directions.

2. Literature review

Consistent with the highlighted literature in the introduction, the extant contemporary literature on insurance in Africa (which has not focused on the nexus between inequality and insurance) can be discussed in two main strands[3]. One has focused on the determinants of life insurance in the continent, while the other has been concerned with linkages between insurance penetration and development outcomes.

In the first strand on determinants of insurance penetration, Guerineau and Sawadogo (2015) assess drivers of life insurance in sub-Saharan Africa (SSA) with focus on twenty countries in SSA and data for the period 1996-2011. The empirical strategy adopted by the authors (i.e. an instrumental variable technique) enables them to account for potential issues of endogeneity. The findings show a positive relationship between income per capita and life insurance premium. The improvement of life insurance schemes is negatively linked with young dependency and life expectancy ratios whereas the following determinants are positively associated with life insurance, namely: government stability, old dependency ratio and the protection of property. The study also maintains that life insurance is still viewed as a luxury commodity in the sub-region.

Motivations for the demand for life insurance have also been investigated by Zerriaa *et al*. (2017). Focusing on Tunisia using annual data for the period 1990-2014, the authors find that inflation and interest rates do not significantly determine the outcome variable. Conversely, pension expenditures have a negative effect whereas life expectancy, dependency, urbanization, income and financial development positively drive life insurance.

Characteristics that are convenient for the development of life insurance are assessed by Alhassan and Biekpe (2016b) in thirty-one African countries for the period 1996-2010. The corresponding findings reveal that relative to financial determinants, demographic factors are associated with a higher explanatory power. In addition, the findings also reveal that life insurance consumption is diminished by dependency, inflation and life expectancy while positive associations are apparent from the following determinants: institutional quality, financial development and health expenditure.

In the second strand, the causal linkage between insurance and economic prosperity has been examined by Akinlo (2015) in a sample of thirty countries in SSA over the period

[3]The papers engaged in this section do not specifically deal with inequality. The purpose of the section is to substantiate the highlighted literature in the introduction. Accordingly, the study is being positioned on inequality because of the absence of literature focusing on the nexus between insurance and inequality in Africa.

1995-2011. Using a panel heterogeneous causality analytical technique, the findings reveal evidence of bidirectional causality between insurance and economic prosperity.

In another study on the relationship between the penetration of insurance and economic development, linkages between efficiency, productivity and scale economies in the non-life insurance market are examined by Alhassan and Biekpe (2015) using data from South Africa over the period 2007-2012. With logistic, bootstrapped and data envelopment analysis, the results show that: approximately 20% of insurers optimally perform their operations whereas non-life insurers are associated with about 50% inefficiency. The findings reveal that improvements in productivity are contingent on technological ameliorations as well as evidence of a non-monotonic impact of size on constant returns to scale and efficiency. Furthermore, the findings confirm the relevance of leverage, reinsurance and product line diversification in determining constant returns to scale and efficiency.

Alhassan and Biekpe (2016a) in another research have examined the nexus between economic prosperity and the development of insurance in eight African countries (Algeria, Gabon, Kenya, Madagascar, Mauritius, Morocco, Nigeria and South Africa) for the period 1990-2010. Employing an autoregressive distributed lag (ARDL) empirical strategy; the authors establish a long term linkage between economic growth and the insurance market in South Africa, Kenya, Nigeria, Morocco and Mauritius. Moreover, from a vector error correction model (VECM) empirical setting, evidence of bidirectional causality is revealed in Morocco, mixed findings are apparent for Gabon whereas a unidirectional causality is found in Madagascar and Algeria.

3. Data and methodology

3.1 Data

The study is focused on 42 countries in Sub-Saharan Africa over the period 2004-2014[4]. The corresponding temporal and geographical scopes of the study are restricted by constraints in data availability at the time of the study. The data come from three main sources, notably: (i) World Development Indicators (WDI) of the World Bank for a control variable (i.e. remittances) ; (ii) the Financial Development and Structure Database (FDSD) of

[4]The 42 countries include: "Angola, Benin, Botswana, Burundi, Cabo Verde, Cameroon, Central African Republic, Chad, Comoros, Congo Democratic Republic, Congo Republic, Côte d'Ivoire, Djibouti, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritius, Mozambique, Namibia, Niger, Nigeria, Rwanda, Sao Tome & Principe, Senegal, Seychelles, Sierra Leone, South Africa, Sudan, Swaziland, Tanzania, Togo, Uganda and Zambia".

the World Bank for the insurance premiums (i.e. life insurance and non-life insurance) and a control variable (i.e. financial depth); (iv) the Global Consumption and Income Project (GCIP) for the inequality variables (i.e. the Gini coefficient, the Atkinson index and the Palma ratio).

Consistent with the contemporary literature on inequality, three main inequality indicators are adopted by the study (Tchamyou *et al.*, 2019a; Meniago & Asongu, 2018). The indicators include: (i) the Gini coefficient which reflects the distribution of wealth across the population. However, the main drawback in the indicator is that it fails to capture extreme values in the inequality distribution (Naceur & Zhang, 2016). Hence, in order to control for tails of the inequality distribution, the Gini coefficient is complemented with two more inequality indicators that are designed to capture extreme values of the inequality distribution, namely: the Palma ratio and the Atkinson index. (ii) The Atkinson index is an indicator of income inequality which measures the percentage of total income that a specific society would forego in an attempt to have more income equality among citizens. (iii) The Palma ratio denotes national income shares of the top 10% of households to the bottom 40%.

All the insurance premiums provided by the FDSD of the World Bank are considered in the analysis, notably: life insurance and non-life insurance. The choice of these two premiums is also motivated by the engaged literature in section 2 (Ioncică *et al.*, 2012; Akinlo, 2015; Guerineau & Sawadogo, 2015; Alhassan & Biekpe, 2015, 2016a, 2016b; Zerriaa *et al.*, 2017; Asongu & Odhiambo, 2020a, 2020b)[5].

Two control variables are adopted in order to account for variable omission bias, namely: remittances and government expenditure. Variables in the conditioning information set are limited to two because a preliminary analysis shows that accounting for more control variables generates estimations that fail to pass post-estimation diagnostic tests in the Generalized Method of Moments (GMM) results. Accordingly, even when instruments are collapsed in the specification process, the involvement of more than two control variables still leads to instrument proliferation. The limitation to two control variables is not an issue for the robustness of the GMM specifications because there is a strand of the GMM literature that

[5]The adoption of life and non-life insurance premiums is based on a review of the attendant literature. For instance Ioncica (2012), who focuses on the insurance market in Romania, broadly confirms the two types of insurance classifications "*Formal education is also associated with status and with a demand for security and protection of life, health and properties of the individual through insurance*" (Ioncica, 2012, p. 4155). Hence, when reviewing the literature, we are not exclusively concerned with phraseological mentions of the types of insurance premiums used in the study. We delve deeper to understand whether the insurance discussion can be classified into the life and non-life insurance premiums used in the study.

does not employ control variables in order to limit instrument proliferation and avoid inefficient estimates (Osabuohien & Efobi, 2013; Asongu & Nwachukwu, 2017b).

Among the selected control variables, remittances are expected to averagely reduce income inequality. However, when the whole distribution of income distribution is considered, such that wealthy and less wealthy factions of the population as articulated in the modeling exercise, it is likely for remittances to increase inequality. Hence, in the light of the definitions, conceptions and measurements of the inequality indicators, remittances can reduce the Gini coefficient and have the opposite effect on the Atkinson index and Palma ratio. This discourse on the contingency of the effect remittances on the heterogeneity of inequality indicators is consistent with the attendant inequality literature. According to Anyanwu (2011) and Meniago and Asongu (2018), most of the population remitting funds to Africa are from wealthier factions of the African society. This is essentially because those migrating abroad are largely from wealthy backgrounds which, have the associated financial resources for visa processing and related administrative travel expenses.

Financial depth in the perspective of money supply has been established to be pro-poor in recent African inequality literature (Tchamyou *et al.*, 2019a). The definitions and sources of variables are provided in Appendix 1 whereas the summary statistics is disclosed in Appendix 2. The correlation matrix is covered by Appendix 3.

3.2 Methodology

Consistent with contemporary literature (Asongu & Minkoua, 2018; Zhang et al., 2019; Li et al., 2014, 2016; Kou et al., 2012, 2014, 2016, 2019a, 2019b), the adopted estimation technique is consistent with data behaviour. The GMM estimation approach is adopted for four fundamental reasons. First, the number of cross sections (i.e. sampled countries) is higher compared to the number of time periods appearing in each cross section. Therefore, since 42 (i.e. number of countries) is substantially higher than corresponding number of years (i.e. 11 or 2004 to 2014) in each cross section, the adopted estimation strategy is appropriate. It follows that the N(42)>T(11) condition for the employment of the GMM approach is fulfilled. Second, given that persistence is also a condition for the adoption of the GMM technique, we explore the nexuses between the identified inequality indicators and their first lags to confirm that the corresponding correlations are higher than the rule of thumb threshold of 0.800 used to ascertain the persistence of an outcome variable in the extant GMM and inequality literature (Tchamyou et al., 2019b). Accordingly, the study finds that the corresponding correlations for the Atkinson index, the Palma ratio and the Gini coefficient are respectively, 0.958, 0.964 and 0.918. Third, the panel nature of the data structure allows the estimation approach to account for cross-country differences in the specifications. Fourth, the concern of endogeneity is addressed from two main perspectives. On the one hand, the issue of reverse causality or simultaneity is tackled by using internal instruments. On the other hand, by involving time invariant indicators in the conditioning information set, the estimation captures the unobserved heterogeneity.

In the light of narratives that traditional GMM approaches produce less efficient estimated coefficients, this study adopts the Roodman (2009a, 2009b) extension of Arellano and Bover (1995) because it has been established to produce more efficient estimates and restrict instrument proliferation (Love & Zicchino, 2006; Baltagi, 2008; Asongu & Nwachukwu, 2016b; Boateng *et al.*, 2018).

The following equations in level (1) and first difference (2) summarise the standard *system* GMM estimation procedure.

$$I_{i,t} = \sigma_0 + \sigma_1 I_{i,t-\tau} + \sigma_2 IS_{i,t} + \sigma_3 ISIS_{i,t} + \sum_{h=1}^{2} \delta_h W_{h,i,t-\tau} + \eta_i + \xi_t + \varepsilon_{i,t} \qquad (1)$$

$$\begin{aligned} I_{i,t} - I_{i,t-\tau} &= \sigma_1 (I_{i,t-\tau} - I_{i,t-2\tau}) + \sigma_2 (IS_{i,t} - IS_{i,t-\tau}) + \sigma_3 (ISIS_{i,t} - ISIS_{i,t-\tau}) \\ &+ \sum_{h=1}^{2} \delta_h (W_{h,i,t-\tau} - W_{h,i,t-2\tau}) + (\xi_t - \xi_{t-\tau}) + (\varepsilon_{i,t} - \varepsilon_{i,t-\tau}) \end{aligned} \qquad (2)$$

where, $I_{i,t}$ is an inequality indicator (i.e. Gini coefficient, Atkinson index and Palma ratio) of country i in period t, σ_0 is a constant, IS entails insurance (life insurance and non-life insurance), $ISIS$ denote quadratic interactions between insurance premiums ("life insurance" × "life insurance", "non-life insurance" × "non-life insurance"), W is the vector of control variables (remittances and financial depth), τ represents the coefficient of auto-regression which is one within the framework of this study because a year lag is enough to capture past information, ξ_t is the time-specific constant, η_i is the country-specific effect and $\varepsilon_{i,t}$ the error term.

Consistent with the attendant literature, the study discusses identification and exclusion restrictions properties underpinning the GMM strategy (Tchamyou & Asongu, 2017; Tchamyou *et al.*, 2019). These are essential for robust GMM estimations. All explanatory variables are considered as predetermined variables and the years or time invariant variables are considered as strictly exogenous, in accordance with recent empirical literature, notably: Boateng *et al.* (2018) and Asongu and Nwachukwu (2016c). The identification strategy is also supported by Roodman (2009b)[6] who has argued that it is unfeasible for the time invariant variables to become endogenous after a first difference.

In the light of the above identification process, in the empirical results section of this study, the exclusion restriction assumption is examined with the Difference in Hansen Test (DHT) for instrument exogeneity. Like in the empirical literature based on the standard instrumental variable (IV) approach (see Beck *et al.*, 2003; Asongu & Nwachukwu, 2016d), a rejection of the null hypothesis of the over-identifying restrictions test is an indication that the strictly exogenous variables or instruments explain the outcome variable beyond the proposed channels or endogenous explaining variables. Hence, the validity of the exclusion restriction assumption is validated when the null hypothesis of the DHT is not rejected.

4. Empirical results

4.1 Presentation of results

The results are disclosed in this section. While Table 1 focuses on life insurance, Table 2 is concerned with non-life insurance. For either table, three specifications are apparent for each of the three inequality indicators used in the study. The specifications are tailored such that there is a primary non-quadratic specification and a secondary quadratic specification (i.e. involving the interaction of insurance premiums). While the primary specification is meant to assess the effect of insurance on inequality, the secondary specification investigates the relevance of increasing insurance on inequality. For all specifications, four information criteria are employed to assess the validity of the GMM model with forward orthogonal deviations[7]. Based on these criteria, all the estimated models are valid.

"Insert Table 1 here"

Given that the main objective of this study is linked to the secondary specifications, the overall effect of enhancing insurance on inequality is assessed by computing the net effect from unconditional and conditional or marginal effects of insurance penetration. For instance in the third column of Table 1, the net impact from increasing life insurance is 0.0026 (2×[-

[6]Hence, the procedure for treating *ivstyle* (years) is 'iv (years, eq(diff))' whereas the *gmmstyle* is employed for predetermined variables.

[7] "*First, the null hypothesis of the second-order Arellano and Bond autocorrelation test (AR (2)) in difference for the absence of autocorrelation in the residuals should not be rejected. Second the Sargan and Hansen over-identification restrictions (OIR) tests should not be significant because their null hypotheses are the positions that instruments are valid or not correlated with the error terms. In essence, while the Sargan OIR test is not robust but not weakened by instruments, the Hansen OIR is robust but weakened by instruments. In order to restrict identification or limit the proliferation of instruments, we have ensured that instruments are lower than the number of cross-sections in most specifications. Third, the Difference in Hansen Test (DHT) for exogeneity of instruments is also employed to assess the validity of results from the Hansen OIR test. Fourth, a Fisher test for the joint validity of estimated coefficients is also provided*" (Asongu & De Moor, 2017, p.200).

0.0002× 0.881] + [0.003]). In the computation, the mean value of life insurance is 0.881, the unconditional effect of life insurance is 0.003 while the conditional effect from enhancing life insurance is -0.0002. The net impact on the Gini coefficient is robust to the effect on the Atkinson index.

In the same vein, in the last column of Table 2, the net impact from increasing non-life insurance is 0.0587 (2×[-0.445× 0.798] + [0.761). In the computation, the mean value of non-life insurance is 0.798, the unconditional effect of life insurance is 0.761while the conditional effect from enhancing non-life insurance is -0.445.

"Insert Table 2 here"

The following findings can be established in Tables 1-2. Life insurance increases inequality (see the Gini coefficient) and increasing life insurance has a net positive effect on inequality (see, the Gini coefficient and the Atkinson index). Non-life insurance reduces inequality (see the Gini coefficient) and increasing non-life insurance has a net positive effect on inequality (see the Palma ratio). The significant control variables have the expected signs.

4.2 Extension with policy thresholds

An extension with threshold analysis is relevant in the perspective that, while the net effects are consistently positive on inequality, the corresponding marginal effects used to compute the net effects are consistently negative. This implies that, there is a diminishing effect on inequality from increasing insurance. It further implies that at a certain threshold of insurance penetration, the net effect of increasing insurance penetration on inequality is zero, such that above the threshold, increasing insurance has a negative effect on inequality. In other words, increasing insurance above the threshold should completely dampen the positive unconditional effect of insurance on inequality. However, in order for the thresholds to be economically meaningful and policy-relevant, they should be situated within acceptable limits disclosed by the summary statistics, notably: between the minimum and maximum limits in the corresponding summary statistics.

The above conception and definition of threshold are consistent with the attendant literature , notably: critical masses at which further carbon dioxide emissions can compromise inclusive development (Asongu, 2018); minimum requirements for desired effects (Cummins, 2000); critical masses for favorable findings (Roller & Waverman, 2001; Batuo, 2015) and conditions for U-shaped and inverted U-shaped patterns (Ashraf & Galor, 2013).

From Table 1, the negative threshold of life insurance is 7.500 (0.003/ [2×0.0002]). Hence, 7.500 of life insurance premium (% of GDP) is the minimum value required for life insurance to negatively affect inequality in sampled countries. This threshold makes economic sense and has policy relevance because it is within the maximum limit of 12.220 % of life insurance imposed by the summary statistics. Policy makers should therefore increase life insurance penetration above the computed threshold in order for insurance to reduce inequality.

In the same vein, the negative threshold of non-life insurance is 0.855 (0.761/ [2×0.445]). Hence, 0.855 of non-life insurance premium (% of GDP) is the minimum value required for non-life insurance to negatively affect inequality in the sampled countries. This threshold makes economic sense and has policy relevance because it is within the maximum limit of 2.774% of non-life insurance provided in the summary statistics. Policy makers should therefore increase non-life insurance penetration above this threshold in order for non-life insurance to reduce inequality.

The findings can be elucidated with the concept informal insurance in the light of attendant literature (Ligon *et al.*, 2002; Dupas & Robinson, 2013; De Magalhaes & Santaeulalia 2018; De Magalhaes et al., 2019). Accordingly, understanding the main difference between life insurance and other insurance schemes (e.g. non-life insurance) is important in elucidating the findings. In essence, life insurance works as savings and is a way for the rich to accumulate assets. This is relevant because, given that there are savings constraints, life insurance provides a way of slackening these savings constraints. Hence, the results that life insurance increases inequality is broadly consistent with studies supporting the perspective that life insurance is used by the rich to accumulate assets (De Magalhaes & Santaeulalia 2018; Dupas & Robinson, 2018) and, by extension, *ceteris paribus*, the accumulation of more wealth by the rich naturally increases income inequality. Moreover, the findings that non-life insurance decreases inequality is traceable to perspective of non-life insurance smoothing consumption over the lifecycle (De Magalhaes *et al.*, 2019). This clarification on non-life insurance should also be understood in the perspective that since most of the sampled countries are poor countries, informal forms of savings or insurance are quite substantial (Carroll, 1997; Kaplan & Violante, 2010) even to consumption and income distributions in such poor economies (Ligon *et al.*, 2002).

5. Conclusion and future research directions

In order to complement the extant literature on insurance penetration in sub-Saharan Africa, this study has investigated how inequality is affected by insurance penetration. Contingent on data availability constraints at the time of the study, the research examines a panel of 42 countries in the sub-region over the period 2004-2014. Three inequality variables (i.e. the Gini coefficient, the Atkinson index and the Palma ratio) and two insurance premiums (i.e. life insurance and non-life insurance) are used for the purpose of the study. The GMM is used as empirical strategy. The findings show that life insurance has a positive impact on the Gini coefficient while increasing life insurance induces a positive overall incidence on both the Atkinson index and the Gini coefficient. The incidence of non-life insurance on the Gini coefficient is negative and boosting non-life insurance leads to an overall net positive impact on the Palma ratio.

In order to provide the room for policy implications, the study is extended by establishing critical masses at which boosting insurance can completely eliminate the overall positive net impacts on inequality. The extended analyses show that a threshold of 7.500 life insurance premiums (% of GDP) is required for life insurance to affect inequality negatively, whereas a threshold of 0.855 non-life insurance premiums (% of GDP) is needed for non-life insurance to negatively impact inequality. These thresholds make economic sense and have policy relevance because they are within the acceptable ranges of life and non-life insurance.

Future studies can use relevant empirical strategies to established country-specific policy thresholds. This recommendation is motivated by the fact that country-specific cases are eliminated from the GMM specification in order to control for endogeneity.

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Table 1: Inequality and Life Insurance

	Dependent variable: Inequality dynamics					
	Gini Coefficient		Atkinson Index		Palma Ratio	
Constant	0.012	**0.055*** **	-0.012	**0.022***	0.098	**0.248*** **
	(0.470)	**(0.000)**	(0.570)	**(0.067)**	(0.678)	**(0.023)**
Gini Coefficient (-1)	**0.986*** **	**0.926*** **	---	---	---	---
	(0.000)	**(0.000)**				
Atkinson Index (-1)	---	---	**1.031*** **	**0.990*** **	---	---
			(0.000)	**(0.000)**		
Palma Ratio(-1)	---	---	---	---	**1.054*** **	**1.022*** **
					(0.000)	**(0.000)**
Life Insurance (LI)	**0.002***	**0.003*** **	0.0003	**0.003***	-0.017	0.035
	(0.086)	**(0.037)**	(0.779)	**(0.097)**	(0.631)	(0.424)
LI×LI	---	**-0.0002*** **		**-0.0002*** **	---	-0.001
		(0.036)		**(0.033)**		(0.613)
Financial Depth	-0.0001	**-0.0004*** **	-0.0002	**-0.0004*** **	**-0.011*** **	**-0.010*** **
	(0.491)	**(0.000)**	(0.247)	**(0.000)**	**(0.010)**	**(0.000)**
Remittances	**-0.0004*** **	**-0.0005*** **	-0.00005	-0.00002	-0.001	-0.001
	(0.001)	**(0.000)**	(0.823)	(0.745)	(0.736)	(0.596)
Time Effects	Yes	Yes	Yes	Yes	Yes	Yes
Net Effects	na	0.0026	na	0.0026	na	na
AR(1)	(0.093)	(0.098)	(0.095)	(0.076)	(0.095)	(0.092)
AR(2)	**(0.217)**	**(0.197)**	**(0.835)**	**(0.845)**	**(0.392)**	**(0.385)**
Sargan OIR	**(0.876)**	**(0.926)**	(0.025)	(0.035)	**(0.407)**	**(0.374)**
Hansen OIR	**(0.883)**	**(0.344)**	**(0.725)**	**(0.180)**	**(0.812)**	**(0.352)**
DHT for instruments						
(a)Instruments in levels						
H excluding group	**(0.719)**	**(0.623)**	**(0.567)**	**(0.643)**	**(0.623)**	**(0.696)**
Dif(null, H=exogenous)	**(0.812)**	**(0.215)**	**(0.677)**	(0.085)	**(0.762)**	**(0.195)**
(b) IV (years, eq(diff))						
H excluding group	**(0.910)**	**(0.809)**	**(0.725)**	**(0.936)**	**(0.574)**	**(0.833)**
Dif(null, H=exogenous)	**(0.679)**	**(0.115)**	**(0.569)**	(0.024)	**(0.793)**	**(0.111)**
Fisher	**5244.31*** **	**105832.47*** **	**4256.60*** **	**235044.14*** **	**2507.20*** **	**79103.27*** **
Instruments	28	32	28	32	28	32
Countries	35	35	35	35	35	35
Observations	261	261	261	261	261	261

***,**,*: significance levels at 1%, 5% and 10% respectively. DHT: Difference in Hansen Test for Exogeneity of Instruments Subsets. Dif: Difference. OIR: Over-identifying Restrictions Test. The significance of bold values is twofold. 1) The significance of estimated coefficients and the Wald statistics. 2) The failure to reject the null hypotheses of: a) no autocorrelation in the AR(1) & AR(2) tests and; b) the validity of the instruments in the Sargan and Hansen OIR tests. The mean of Life Insurance is 0.881. na: not applicable because at least one estimated coefficient necessary for the computation of the net effect is not significant.

Table 2: Inequality and Non-Life Insurance

	Dependent variable: Inequality dynamics					
	Gini Coefficient		**Atkinson Index**		**Palma Ratio**	
Constant	**0.052***** **(0.003)**	**0.025**** **(0.013)**	-0.010 (0.719)	-0.015 (0.303)	**0.654**** **(0.011)**	-0.021 (0.931)
Gini Coefficient (-1)	**0.927***** **(0.000)**	**0.963***** **(0.000)**	---	---	---	---
Atkinson Index (-1)	---	---	**1.043***** **(0.000)**	**1.036***** **(0.000)**	---	---
Palma Ratio(-1)	---	---	---	---	**0.974***** **(0.000)**	**1.049***** **(0.000)**
Non Life Insurance (NLI)	**-0.005*** **(0.083)**	0.008 (0.407)	-0.010 (0.109)	0.017 (0.295)	-0.054 (0.824)	**0.761**** **(0.028)**
NLI×NLI	---	-0.006 (0.115)	---	**-0.013**** **(0.032)**	---	**-0.445***** **(0.003)**
Financial Depth	-0.0002 (0.108)	-0.0001 (0.139)	-0.0003 (0.118)	**-0.0003**** **(0.019)**	**-0.016***** **(0.007)**	**-0.016**** **(0.000)**
Remittances	0.0002 (0.103)	**-0.0002***** **(0.007)**	0.0003 (0.547)	0.0002 (0.400)	**0.033*** **(0.064)**	**0.011**** **(0.048)**
Time Effects	Yes	Yes	Yes	Yes	Yes	Yes
Net Effects	na	na	na	na	na	0.0587
AR(1)	**(0.100)**	(0.098)	(0.087)	(0.085)	(0.098)	(0.097)
AR(2)	**(0.237)**	**(0.220)**	**(0.943)**	**(0.966)**	**(0.432)**	**(0.455)**
Sargan OIR	**(0.873)**	**(0.879)**	(0.041)	(0.039)	**(0.655)**	**(0.606)**
Hansen OIR	**(0.749)**	**(0.674)**	**(0.863)**	**(0.951)**	**(0.472)**	**(0.727)**
DHT for instruments						
(a)Instruments in levels						
H excluding group	**(0.669)**	**(0.708)**	**(0.594)**	**(0.658)**	**(0.427)**	**(0.585)**
Dif(null, H=exogenous)	**(0.640)**	**(0.518)**	**(0.853)**	**(0.953)**	**(0.456)**	**(0.673)**
(b) IV (years, eq(diff))						
H excluding group	**(0.505)**	**(0.449)**	**(0.455)**	**(0.736)**	**(0.253)**	**(0.470)**
Dif(null, H=exogenous)	**(0.754)**	**(0.734)**	**(0.924)**	**(0.944)**	**(0.626)**	**(0.788)**
Fisher	**1251.46*****	**9467.04*****	**326.19*****	**2503.93*****	**531.59*****	**1936.34*****
Instruments	28	32	28	32	28	32
Countries	36	36	36	36	36	36
Observations	279	279	279	279	279	279

***,**,*: significance levels at 1%, 5% and 10% respectively. DHT: Difference in Hansen Test for Exogeneity of Instruments Subsets. Dif: Difference. OIR: Over-identifying Restrictions Test. The significance of bold values is twofold. 1) The significance of estimated coefficients and the Wald statistics. 2) The failure to reject the null hypotheses of: a) no autocorrelation in the AR(1) & AR(2) tests and; b) the validity of the instruments in the Sargan and Hansen OIR tests. The mean of Non Life Insurance is 0.798. na: not applicable because at least one estimated coefficient necessary for the computation of the net effect is not significant.

Appendices

Appendix 1: Definitions of Variables

Variables	Signs	Definitions of variables (Measurements)	Sources
Income Inequality	Gini Coefficient	*"The Gini coefficient is a measurement of the income distribution of a country's residents"*.	GCIP
	Atkinson Index	*"The Atkinson index measures inequality bydetermining which end of the distribution contributed most to the observed inequality"*.	GCIP
	Palma Ratio	*"The Palma ratio is defined as the ratio of the richest 10% of the population's share of gross national income divided by the poorest 40%'s share"*.	GCIP
Insurance	LifeIns	Life Insurance Premium Volume to GDP (%)	FDSD
	NonLifeIns	Non-life Insurance Premium Volume to GDP (%)	FDSD
Financial Depth	FinD	Money Supply (% of GDP)	FDSD
Remittances	Remit	Remittance inflows to GDP (%)	WDI

WDI: World Bank Development Indicators of the World Bank. FDSD: Financial Development and Structure Database of the World Bank. GCIP: Global Consumption and Income Project.

Appendix 2: Summary statistics (2004-2014)

	Mean	SD	Minimum	Maximum	Observations
Gini Coefficient	0.586	0.034	0.488	0.851	461
Atkinson Index	0.705	0.058	0.509	0.834	461
Palma Ratio	6.457	1.477	3.015	14.434	461
Life Insurance	0.881	2.126	0.0006	12.220	346
Non Life Insurance	0.798	0.536	0.005	2.774	367
Financial Depth	32.022	19.431	4.383	99.958	440
Remittances	4.313	6.817	0.00003	50.818	416

S.D: Standard Deviation.

Appendix 3:Correlation matrix (uniform sample size: 342)

Gini	Atkinson	Palma	LifeIns	NonLifeIns	Fin.D	Remit	
1.000	0.857	0.952	0.038	0.084	-0.249	0.010	Gini
	1.000	0.925	0.028	0.159	-0.212	0.159	Atkinson
		1.000	0.055	0.112	-0.226	0.079	Palma
			1.000	0.747	0.186	-0.019	LifeIns
				1.000	0.517	0.156	NonLifeIns
					1.000	0.131	Fin.D
						1.000	Remit

Gini :the Gini Coefficient. Atkinson :the Atkinson Index. Palma: the Palma Ratio. LifeIns: Life Insurance. NonLifeIns: Non Life Insurance. Fin.D: Financial Depth. Remit: Remittances.